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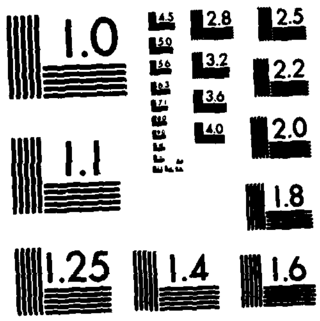

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Report No. 5192

Structure-Mapping: A Theoretical Framework for Analogy

December 1982

Prepared for:
Office of Naval Research
Personnel and Training Research Programs

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A theory of analogy must describe how the meaning of an analogy is derived from the meanings of its parts. In the structure-mapping theory, the interpretation rules are characterized as implicit rules for mapping knowledge about a base domain into a target domain. Two important features of the theory are (1) the rules depend only on syntactic properties of the knowledge representation, and not on the specific content of the domains; and (2) the theoretical framework allows analogies to be

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Two mapping principles are described: (1) Relations between objects, rather than attributes of objects, are mapped from base to target; and (2) The particular relations mapped are determined by systematicity, as defined by the existence of higher-order relations.

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Abstract

A theory of analogy must describe how the meaning of an analogy is derived from the meanings of its parts. In the structure-mapping theory, the interpretation rules are characterized as implicit rules for mapping knowledge about a base domain into a target domain. Two important features of the theory are (1) the rules depend only on syntactic properties of the knowledge representation, and not on the specific content of the domains; and (2) the theoretical framework allows analogies to be distinguished cleanly from literal similarity statements, applications of general laws, and other kinds of comparisons.

Two mapping principles are described: (1) Relations between objects, rather than attributes of objects, are mapped from base to target; and (2) The particular relations mapped are determined by systematicity, as defined by the existence of higher-order relations.

Structure-Mapping: A Theoretical Framework for Analogy

When people hear an analogy such as "An electric battery is like a reservoir" how do they derive its meaning? We might suppose that they simply apply their knowledge about reservoirs to batteries; and that the greater the match, the better the analogy. Such a "degree of overlap" approach seems reasonably correct for literal similarity comparisons. In Tversky's (1977) elegant contrast model, the similarity between A and B is greater the greater the size of the intersection (A B) of their feature sets and the less the size of the two complement sets (A - B) and (B - A).[2] However, although the degree-of-overlap model appears to work well for literal similarity comparisons, it does not provide a good account of analogy. The strength of an analogical match does not seem to depend on the overall degree of featural overlap; not all features are equally relevant to the interpretation. Only certain kinds of mismatches count for or against analogies. For example, we could not support the battery-reservoir analogy by remarking (even if true) that batteries and reservoirs both tend to be cylindrical; nor does it weaken the analogy to show that their shapes are different. The essence of the analogy between batteries and reservoirs is that both store potential energy, release that energy to provide power for systems, etc. We can be quite satisfied with the analogy in spite of the fact that the average battery differs from the average reservoir in size, shape, color, and substance.

As another example of the selectiveness of analogical mapping, consider the simple arithmetic analogy 3:6::2:4. We do not care how many features 3 has in common with 2, nor 6 with 4. It is not the overall number of shared versus nonshared features that counts here, but only the relationship "twice as great as" that holds between 3 and 6 and also between 2 and 4. To underscore the implicit selectiveness of the feature match, note that we do not consider the analogy 3:6::2:4 better or more apt than the analogy 3:6::200:400, even though by most accounts 3 has more features in common with 2 than with 200.

A theory based on the mere relative numbers of shared and non-shared predicates cannot provide an adequate account of analogy, nor, therefore, a sufficient basis for a general account of relatedness. In the structure-mapping theory, a simple but powerful distinction is made among predicate types, that allows us to state which ones will be mapped. The basic intuition is that an analogy is fundamentally an assertion that a relational structure that normally applies in one domain can be applied in another domain. Before laying out the theory. a few preliminaries are necessary.

Preliminary Assumptions and Points of Emphasis

1. Domains and situations are psychologically viewed as systems of objects, object-attributes and relations between objects.[3]

2. Knowledge is represented here as propositional networks of nodes and predicates (cf. Miller & Johnson-Laird, 1979; Norman, Rumelhart, & the LNR Group, 1975; Rumelhart & Ortony. 1977; Schank & Abelson, 1977). The nodes represent concepts treated as wholes; the predicates applied to the nodes express propositions about the concepts.

3. Two essentially syntactic distinctions among predicate types will be important. The first distinction is between object attributes and relationships. This distinction can be made explicit in the predicate structure: attributes are predicates taking one argument, and relations are predicates taking two or more arguments. For example, COLLIDE (x,y) is a relation, while LARGE (x) is an attribute.[4]

The second important syntactic distinction is between first-order predicates (taking objects as arguments) and second- and higher-order predicates (taking propositions as arguments). For example, if COLLIDE (x,y) and STRIKE (y,z) are first-order predicates, CAUSE [COLLIDE(x,y), STRIKE (y,z)] is a second-order predicate.

4. These representations, including the distinctions between different kinds of predicates, are intended to reflect the way people construe a situation, rather than what is logically possible.[5]

Structure-mapping: Interpretation Rules

The analogy "A T is (like) a B" conveys that aspects of the hearer's knowledge about B can be applied to T. T will be called the <u>target</u>, since it is the domain being explicated. B will be called the <u>base</u>, since it is the (presumably more familiar) domain that serves as the source of knowledge. Suppose that the hearer's representation of the base domain B can be stated in terms of object nodes $b_1, b_2, \ldots, b_n$ and predicates such as A, R. R'. The hearer knows, or is told,[6] that the <u>target</u> domain has object nodes $t_1, t_2, \ldots, t_m$. In order to understand the analogy, the hearer must map the object nodes of B onto the object nodes of T:

$$M: b_i \dashrightarrow t_i$$

Given these object correspondences, the hearer derives inferences about T by applying predicates valid in the base domain B, using the node substitutions dictated by the object mapping:

$$M: [R(b_i, b_j)] \dashrightarrow [R(t_i, t_j)]$$

Here $R(b_i, b_j)$ is a relation that holds in the base domain B.[7] Higher-order relations, such as $R'(R_1, R_2)$, can also be mapped:

$$M: [R'(R_1(b_i, b_j), R_2(b_k, b_l)] \dashrightarrow$$

$$[R'(R_1(t_i, t_j), R_2(t_k, t_l)]$$

Higher-order relations play an important role in analogy, as is discussed below.

Finally, a distinguishing characteristic of analogy is that attributes (one-place predicates) from B tend not to be mapped into T:

$$[A(b_i)] \not\longrightarrow [A(t_i)].$$

Notice that this discussion has been purely structural; the distinctions invoked rely only on the syntax of the knowledge representation, not on the content. The <u>content</u> of the relations may be static spatial information, as in UNDER(x,y), or FULL(CONTAINER. WATER); or constraint information, as in PROPORTIONAL [(PRESSURE(liquid, source, goal), FLOWRATE(liquid, source, goal)]; or dynamic causal information, as in CAUSE {AND [PUNCTURE(CONTAINER), FULL(CONTAINER. WATER)], FLOW-FROM (WATER. CONTAINER)}.

<u>Kinds of Domain Comparisons</u>

In the structure-mapping framework, the interpretation rules for analogy can be distinguished from those for other kinds of domain comparisons. The syntactic type of the shared versus nonshared predicates determines whether a given comparison is

thought of as analogy, as literal similarity, or as the application of a general law.

In this section, different kinds of domain comparisons are described, using the solar system as a common theme. The top half of Figure 1 shows a partial representation of what might be a person's knowledge of our solar system. (The dotted lines should be ignored for now.) Both object-attributes, such as YELLOW (sun), and relations between objects, such as REVOLVE AROUND (planet, sun) are shown. (The diagram is quite sparse; most of us know much more than is shown here.) Assuming that the hearer has the correct object correspondences, the question is which predicates will be mapped for each type of comparison.

(1) A literal similarity statement is a comparison in which a large number of predicates is mapped from base to target, relative to the number of nonmapped predicates (e.g., Tversky, 1977). The mapped predicates include both object-attributes and relational predicates.

EXAMPLE(1): The X12 star system in the Andromeda nebula is like our solar system.

INTERPRETATION: Intended inferences include both object characteristics--e.g., "The X12 star is YELLOW, MEDIUM-SIZED, etc., like our sun." and relational characteristics, such as "The X12 planets REVOLVE AROUND the X12 star, as in our system."

In a literal similarity comparison, all or most of the predicates shown would be mapped.

(2) An <u>analogy</u> is a comparison in which relational predicates, but few or no object attributes, can be mapped from base to target.

EXAMPLE(2): The hydrogen atom is like our solar system. (Rutherford, 1906)

INTERPRETATION: Intended inferences concern chiefly the relational structure: e.g., "The electron REVOLVES AROUND the nucleus, just as the planets REVOLVE AROUND the sun." but not "The nucleus is YELLOW, MASSIVE, etc., like the sun." The bottom half of Figure 1 shows these mapped relations. If higher-order relations are present in the base, they can be mapped as well: e.g., The hearer might map "The fact that the nucleus ATTRACTS the electron <u>CAUSES</u> the electron to REVOLVE around the nucleus." from "The fact that the sun ATTRACTS the planets <u>CAUSES</u> the planets to REVOLVE AROUND the sun." (This relation is not shown in Figure 1.)

(3) A <u>general law</u> is a comparison in which the base domain is an abstract relational structure. Such a structure would resemble Figure 1, except that the object nodes would be generalized physical entities, rather than particular objects like "sun" and "planet". Predicates from the abstract base domain are mapped into the target domain; there are no nonmapped predicates.

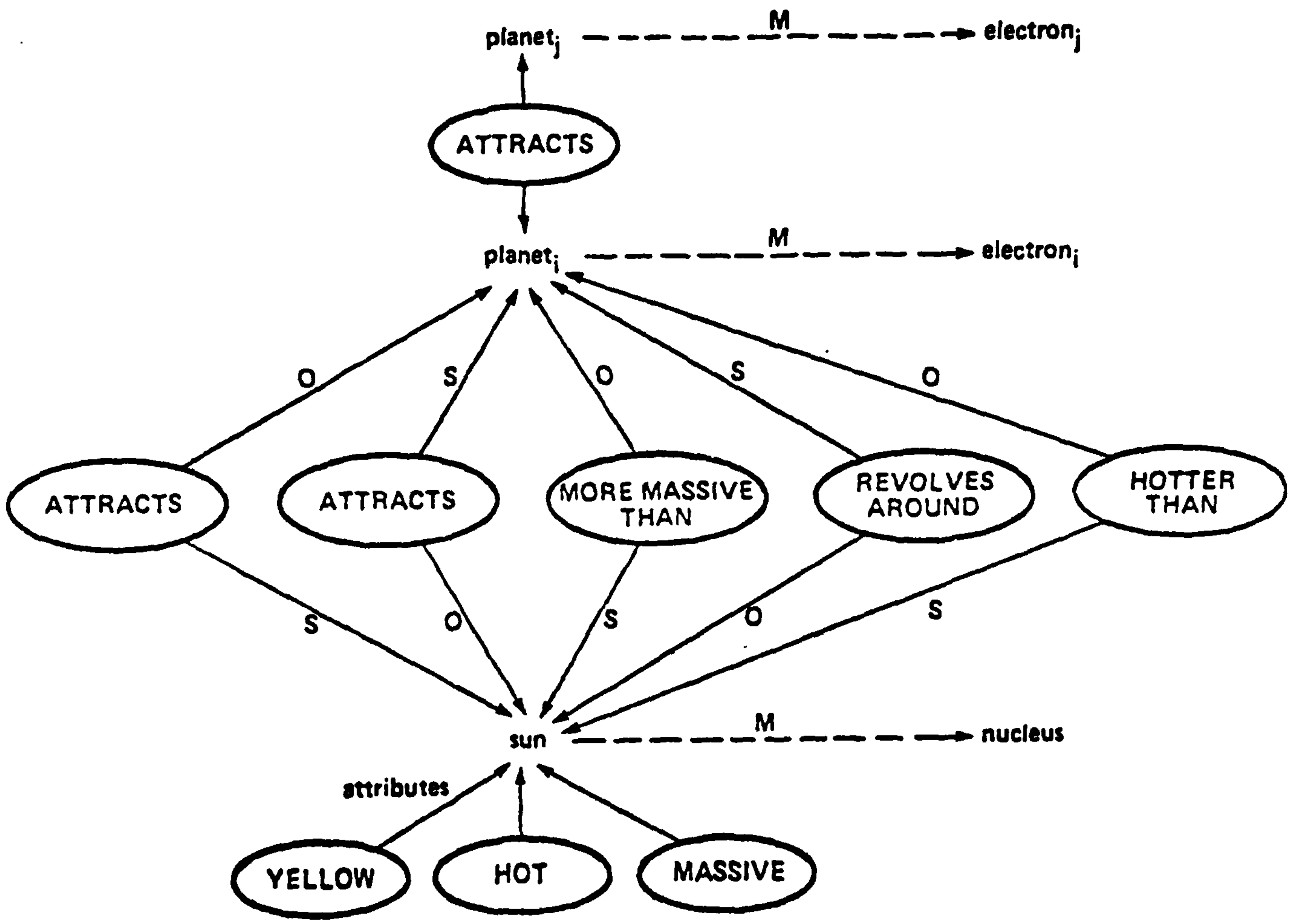

Figure 1. Structure-mapping for the Rutherford analogy: "The atom is like the solar system."

EXAMPLE(3): The hydrogen atom is a central force system.

INTERPRETATION: Intended inferences include "The nucleus ATTRACTS the electron."; "The electron REVOLVES AROUND the nucleus." These are mapped from base propositions such as "The central object ATTRACTS the peripheral object."; or "The less massive object REVOLVES AROUND the more massive object." These intended inferences resemble those for the analogy (Example 2). The difference is that in the analogy there are other base predicates that are not mapped, such as "The sun is YELLOW."

All three kinds of comparison involve substantial overlap in relations, but, except for literal similarity, not in object attributes. What happens if there is strong overlap in objects but not in relations? Let us leave aside single-component matches involving only one object out of many, and instead consider comparisons in which all the objects are shared, but relations between objects are not. The commonest case in which this arises is chronology:

(4) A chronology is a comparison between two time-states of the same domain. The objects at time 1 map onto the objects at time 2. This is the only interesting case in which there are shared objects but no shared relations. The two time-states share object-attributes, but typically not relational predicates.

EXAMPLE(4): Two hydrogen atoms and an oxygen atom will combine to form a water molecule.

INTERPRETATION: Although the same objects--two hydrogen atoms and an oxygen atom--are present in both situations, neither configurational relations nor dynamic relations of the initial situation can be mapped into the final situation. Only the independent qualities of the individual atoms (e.g., their atomic weights) are preserved. Note that such overlap among component objects is not sufficient to produce similarity between systems: Two isolated hydrogen atoms and an oxygen atom do not resemble water, either literally or analogically. Chronology will not concern us further; it is included for completeness, as the limiting case of object overlap with no necessary relational overlap.

Table 1 summarizes these distinctions. Overlap in relations is necessary for any strong perception of similarity between two domains. Overlap in both object attributes and inter-object relationships is seen as literal similarity, and overlap in relationships but not objects is seen as analogical relatedness. Overlap in objects but not relationships may be seen as chronology, but not as similarity. Finally, a comparison with neither attribute overlap nor relational overlap is simply an anomaly.

Table 1

Kinds of Predicates Mapped in Different

Types of Domain Comparison

	No. of attributes mapped to target	No. of relations mapped to target	Example
Literal Similarity	Many	Many	The K5 solar system is like our solar system.
Analogy	Few	Many	The atom is like our solar system.
Abstraction	Few[a]	Many	The atom is a central force system.
Anomaly	Few	Few	Coffee is like the solar system

[a] Abstraction differs from analogy and the other comparisons in having few object-attributes in the <u>base</u> domain as well as few object-attributes in the target <u>domain</u>.

According to this analysis, the contrast between analogy and literal similarity is a continuum, not a dichotomy. Given that two domains overlap in relationships, they are more literally similar to the extent that their object-attributes also overlap. A different sort of continuum applies between analogies and general laws: In both cases, a relational structure is mapped from base to target. If the base representation includes concrete objects whose individual attributes must be left behind in the mapping, the comparison is an analogy. As the object nodes of the base domain become more abstract and variable-like, the comparison is seen as a general law.

Metaphor

A number of different kinds of comparisons go under the term "metaphor." Many (perhaps most) metaphors are predominantly relational comparisons, and are thus essentially analogies. For example, in A. E. Housman's comparison, "I could no more define poetry than a terrier can define a rat.", the object correspondences are terrier--poet and rat--poetry. Clearly, the intended inference is not that the poet is like a terrier, nor certainly that poetry is like a rat, but rather, that the relation between poet and poetry is like the relation between terrier and rat. Again, in Virginia Woolf's simile, "She allowed life to waste like a tap left running." the intent seems to be to convey the relational notion of a person wasting a resource

through neglect, rather than to convey that her life was like running water.

However, not all metaphors are relationally focused; some are predominantly attribute matches. These generally involve shared attributes that are few but striking, and often more salient in the base than in the target (Ortony, 1979): e.g., "She's a giraffe," used to convey that she is tall. Many such metaphors involve conventional vehicles, such as "giraffe" above. or conventional dimensional matches, such as "a deep/shallow idea" (Glucksberg, Gildea & Bookin, 1982; Lakoff & Johnson, 1980). Moreover, metaphors can be mixtures of all of these. Finally, for metaphors that are analyzable as analogies or combinations of analogies, the mapping rules tend to be less regular (Gentner, 1982,a).

Higher-order predicates and systematicity

Relations have priority over object-attributes in analogical matching. However, not all relations are equally likely to be preserved in analogy. For example, in the Rutherford analogy between solar system and atom, the relation MORE MASSIVE THAN (sun, planet) is mapped across to the atom, but the formally similar relation HOTTER THAN (sun, planet) is not. The goal of this section is to characterize this analogical relevance explicitly.

Part of our understanding about analogy is that it conveys a system of connected knowledge, not a mere assortment of independent facts. Such a system can be represented by an interconnected predicate structure in which higher-order predicates enforce connections among lower-order predicates.[8] To reflect this tacit preference for coherence in analogy, I propose the <u>systematicity principle</u>: A predicate that belongs to a mappable system of mutually interconnecting relationships is more likely to be imported into the target than is an isolated predicate.

In the Rutherford model, the set of predicates that forms a mappable system includes the following lower-order relations:

(1) DISTANCE (sun, planet),

(2) ATTRACTIVE FORCE (sun, planet)

(3) REVOLVES AROUND (planet, sun), and

(4) MORE MASSIVE THAN (sun, planet).

One symptom of this systematicity is that changing one of these relations affects the others. For example, suppose we decrease the attraction between sun and planet; then the distance between them will increase. all else being equal. Thus relations (1) and (2) are interrelated. Again, suppose we reverse relation (4), to state that the planet is more massive than the sun; then

we must also reverse relation (3), for the sun would then revolve around the planet.[9] One way of expressing these dependencies among the lower-order relations is as a set of simultaneous constraint equations:

$$F_{grav} = \frac{G m_p m_s}{R^2} = m_p a_p = m_s a_s$$

where F_{grav} is the gravitational force, m_p is the mass of the planet, a_p is the radial acceleration of the planet (and similarly m_s and a_s for the sun), R is the distance between planet and sun, and G is the gravitational constant.

The same interdependencies hold for the atom, if we make the appropriate node substitutions:

(5) DISTANCE (nucleus, electron),

(6) ATTRACTIVE FORCE (nucleus, electron)

(7) REVOLVES AROUND (electron, nucleus), and

(8) MORE MASSIVE THAN (nucleus, electron).

The corresponding equations for the atom are

$$F_{elec} = \frac{-q_e q_n}{R^2} = m_e a_e = m_n a_n$$

where F_{elec} is the electromagnetic force, q_e is the charge on the electron, m_e is the mass of the electron, a_e is the radial acceleration of the electron, R_e is the distance between electron and nucleus, (and similarly for the nucleus), and -1 is the electromagnetic constant.

These equations embody higher-order relations that connect the lower-order relations (1) through (4) into a mutually constraining structure. By the systematicity principle, to the extent that people recognize (however vaguely) that the system of predicates connected with central forces is the deepest, most interconnected mappable system for this analogy, they will favor relations that belong to that system in their interpretations.[10] This is why MORE MASSIVE THAN is preserved while HOTTER THAN is not: Only MORE MASSIVE THAN participates in the central-force system of predicates.

As a final demonstration of the operation of the systematicity principle, consider the analogy "Heat is like water," used to explain heat transfer from a warm house in cold weather. Suppose the hearer's knowledge about water includes two scenarios:

1. AND[CONTAIN(vessel, water), ON-TOP-OF(lid, vessel)]

2. CAUSE {AND [PUNCTURE(vessel), CONTAIN(vessel, water)], FLOW-FROM (water, vessel)}.

These can be paraphrased roughly as follows: (1) The vessel contains water and has a lid; (2) if a vessel that contains water is punctured, water will flow out. Assuming that the hearer has made the obvious object correspondences (water --> heat, vessel --> house and lid --> roof),[11] which scenario will be mapped?

Intuitively, the second scenario is more interesting than the first: (1) conveys merely a static spatial description, while (2) conveys a dynamic causal description. We would like chain (2) to be favored over chain (1), so that dynamic causal knowledge is likely to be present in the candidate set of attempted predications (to use Ortony's (1979) term). We could accomplish this by postulating that analogies select for dynamic causal knowledge, or more generally, for appropriate abstractions. Either of these would be a mistake: The former course limits the scope of analogy unreasonably, and the latter course is both vague, in that "appropriateness" is difficult to define explicitly, and incorrect, in that analogies can also convey inappropriate abstractions.[12] We want our rules for analogical interpretation to choose chain (2) over chain (1), but we want them to operate, at least initially, without appeal to specific content or appropriateness. The systematicity principle offers a way to satisfy both requirements. Dynamic causal

information [e.g., (2)] will usually be represented in a more deeply embedded structure than simple stative information [e.g., (1)]. Thus, by promoting deeply nested relational chains, the systematicity principle operates to promote predicates that participate in causal chains and in other constraint relations. It is a purely syntactic mechanism that guarantees that the set of candidate mappings will be as interesting--in the sense that a mutually interconnected system of predicates is interesting--as the knowledge base allows.

In the next section, empirical support for the structure-mapping theory is briefly discussed. First, however. let us review the performance of the theory against a set of a priori theoretical criteria. The structure-mapping theory satisfies the first requirement of a theory of analogy, that it describe the rules by which the interpretation of an analogy is derived from the meanings of its parts. Further, the rules are such as to distinguish analogy from other kinds of domain comparisons, such as abstraction or literal similarity. Finally, a third feature of the structure-mapping theory is that the interpretation rules are characterizable purely syntactically. That is, the processing mechanism that selects the initial candidate set of predicates to map attends only to the <u>structure</u> of the knowledge representations for the two analogs, and not to the content.

Empirical support

There is research supporting the structure-mapping approach. In one set of studies, subjects wrote out interpretations of analogical comparisons such as "A cigarette is like a time bomb." These interpretations were read to naive judges, who rated each assertion as to whether it was an attribute or a relation. (For a fuller description, see Gentner, 1980b). The results indicated a strong focus on relational information in interpreting analogies. Relational information predominates over attributional information in analogy interpretations, but not in object descriptions generated by the same subjects. Further, a correlation of aptness ratings and relationality ratings revealed that subjects liked the analogies best for which they wrote the greatest degree of relational information.

Other experimental evidence for structure-mapping as part of the psychological process of interpreting complex analogies has included developmental studies (Gentner, 1977a,b; 1980b) and studies of how people use analogies in learning science (Collins & Gentner, in preparation; Gentner, 1980a, 1981; Gentner & Gentner, 1982).

Related research

Complex explanatory analogies have until recently received little attention in psychology, perhaps because such analogies

require fairly elaborate representations of meaning. Studies of analogy in scientific learning and in reasoning have emphasized the importance of shared complex representational structures (Clement, 1981. 1982; Collins & Gentner, in preparation; Gentner, 1980; Gentner & Gentner, 1982; Hesse, 1966; Hobbs, 1979; Hoffman, 1980; Moore & Newell, 1973; Oppenheimer. 1955; Polya, 1973; Riley, 1981; Rumelhart & Norman, 1981; Steels, 1981; Stevens, Collins & Goldin, 1979; VanLehn & Brown, 1980). Although some of this work has been empirically tested, most of it remains in the area of interesting but unvalidated theory. In contrast, much of the psychological experimentation on analogy and metaphor has been either theory-neutral (e.g. Schustack & Anderson, 1979; Verbrugge & McCarrell, 1977) or based on rather simple representations of meaning: e.g., feature-list representations (e.g., Ortony, 1979) or multidimensional space representations (e.g., Rumelhart & Abrahamson, 1973; Tourangeau & Sternberg, 1981). These kinds of representations can deal well with object attributes, but are extremely limited in their ability to express relations between objects, and especially higher-order relations.

Recent work in cognitive science has begun to explore more powerful representational schemes. The Merlin system (Moore & Newell, 1973) featured a mechanism for "viewing x as y" (see also Steels, 1982) which involved explicit comparisons of the shared and nonshared predicates of two situations. Winston (1980, 1981), using a propositional representation system, has simulated

the process of matching a current situation with a previously stored precedent and using the similarity match to justify importing inferences from the precedent to the current situation. Further, in recent work he has investigated importance-dominated matching; here the match between old and new situations is performed by counting only those predicates that occur in causal chains. This requirement is somewhat more restrictive than the structure-mapping principle that participation in any higher-order chain results in preferential mapping. However, it has the similar effect of focussing the matcher on systematic relational structures rather than on haphazard resemblances between situations. One valuable aspect of Winston's work is his modelling of the process of abstracting general rules from the analogical matches. Gick and Holyoak have also emphasized the relationship between analogical matching and the formation of general schemas in an interesting series of studies of transfer in problem-solving (Gick and Holyoak, 1980, in press; Holyoak, in press).

Other researchers have explored specific instances of relational mapping. VanLehn & Brown (1980) have analyzed analogical learning of procedural rules in arithmetic, postulating mapping rules compatible with the rules proposed here. Clement (1981, 1982) has proposed a four-stage series of processes of generating analogical comparisons during problem-solving. Rumelhart & Norman (1981) have used a schema-based

representational system to discuss analogical transfer. Carbonell (1981) has characterized the comprehension of analogy; his approach emphasizes common goals and subgoals as organizing principles. In the main, these accounts are compatible with that given by the structure-mapping theory in each of the problem domains. Relations tend to be preserved across domains with dissimilar object-attributes: e.g., the matching of like procedures that apply to unlike sets of objects (VanLehn and Brown, 1980).

The Analogical Shift Conjecture

Some of the distinctions made here may appear rather academic. To illustrate their potential relevance. let us apply these distinctions to the spontaneous comparisons that people make in the course of learning a domain. An informal observation is that the earliest comparisons are chiefly literal-similarity matches, followed by analogies, followed by general laws. For example, Ken Forbus and I have observed a subject trying to understand the behavior of water flowing through a constricted pipe. His first comparisons were similarity matches, e.g., water coming through a constricted hose. Later, he produced analogies such as a train speeding up or slowing down, and balls banging into the walls and transferring momentum. Finally, he arrived at a general statement of the Bernoulli principle, that velocity increases and pressure decreases in a constriction.

This sequence can be understood in terms of the kinds of differences in predicate overlap discussed in this paper. In the structure-mapping framework, we can suggest reasons that the accessibility and the explanatory usefulness of a match may be negatively related. Literal similarity matches are highly accessible, since they can be indexed by object descriptions, by relational structures, or by both. But they are not very useful in deriving causal principles, precisely because there is too much overlap to know what is crucial. Potential analogies are less likely to be noticed, since they require accessing the data base via relational matches; object matches are of no use. However, once found, an analogy should be more useful in deriving the key principles, since the shared data structure is sparse enough to permit analysis. Moreover, if we assume the systematicity principle, then the set of overlapping predicates is likely to include higher-order relations such as CAUSE and IMPLIES. To state a general law requires another step beyond creating a temporary correspondence between unlike domains: the person must create a new relational structure whose objects are so lacking in specific attributes that the structure can be applied across widely different domains. (See Gick & Holyoak, 1980, in press). One speculation is that such general laws can be discovered by comparing two or more analogies, so that the common subparts of the relational structure can be isolated.

Summary

The structure-mapping theory describes the implicit interpretation rules of analogy. The central claims of the theory are that analogy is characterized by the mapping of relations between objects, rather than attributes of objects from base to target; and, further, that the particular relations mapped are those that are dominated by higher-order relations that belong to the mapping (the systematicity claim). These rules have the desirable property that they depend only on syntactic properties of the knowledge representation, and not on the specific content of the domain. Further, this theoretical framework allows us to state the differences between analogies and literal similarity statements, abstractions and other kinds of comparisons.

One implication of the theory is that no treatment of domain relatedness can be complete without distinguishing between object features and relational features: that is, between relational predicates and one-place attributive predicates. Careful analysis of the predicate structure is central to modelling the inferences people make in different kinds of comparisons.

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Footnotes

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[2] According to Tversky (1977), the negative effects of the two complement sets are not equal: for example, if we are asked "How similar is A to B?", the set (B - A)--features of B not shared by A--counts much more than the set (A - B).

[3] These "objects" may be clear entities (e.g. "rabbit"), component parts of a larger object (e.g. "rabbit's ear") or even coherent combinations of smaller units (e.g."herd of rabbits"); the important point is that they function as wholes at a given level of organization.

[4] One clarification is important here. Many attributive

predicates implicitly invoke comparisons between the value of their object and some standard value on the dimension. LARGE (x) implicitly means "X is large for its class." For example, a large star is of a different size than a large mouse. But if LARGE (x) is implicitly interpreted as LARGER THAN (X, prototype-x), then this suggests that many surface attributes are implicitly two-place predicates. Does this invalidate the attribute-relation distinction? I will argue that it does not: that only relations that apply *within* the domain of discourse are psychologically stored and processed as true relations. Thus, a relation such as LARGER THAN (sun, planet), that applies between two objects in the base (or target) domain, is processed as a relation; whereas an implicit attributive comparison, such as LARGER THAN (sun, prototype- star), is processed as an attribute.

[5] Logically, a relation R(a,b,c,) can perfectly well be represented as Q(x), where Q(x) is true just in case R(a,b,c) is true. Psychologically, the representation must be chosen to model the way people think.

[6] Most explanatory analogies are 1-1 mappings, in which m = n. However, there are exceptions (Gentner, 1982,a).

[7] The assumption that predicates are brought across as *identical* matches is crucial to the clarity of this discussion. The position that predicates need only be similar between the

base and the domain (e.g., Hesse, 1966; Ortony, 1979) leads to a problem of infinite regress, with similarity of surface concepts defined in terms of similarity of components, etc,. I will assume instead that similarity can be restated as identity among some number of component predicates.

[8] The <u>order</u> of a relation is determined by the order of its arguments. A first-order relation takes objects as its arguments. A second-order relation has at least one first-order relation among its arguments; and in general an nth order relation has at least one (n-1)th order argument.

[9] This follows from the simultaneous equations below. The radial acceleration of either object is given by the force divided by its own mass; thus the lighter object has the greater radial acceleration. To maintain separation, it must also have a tangential velocity sufficient to keep it from falling into the larger object.

[10] I make the assumption here that partial knowledge of the system is often sufficient to allow a person to gauge its interconnectedness. In the present example, a person may recognize that force, mass and motion are highly interrelated without having full knowledge of the governing equations.

[11] In this discussion I have made the simplifying assumption that, in comprehension of analogy, the hearer starts with the

object correspondences and then maps across the relations. The actual order of processing is clearly variable. If the object assignment is left unspecified, the hearer can use knowledge about matching relations to decide on the object correspondences. Therefore, it is more accurate to replace the statement that the object correspondences are decided before the relational mappings begin with the weaker statement that the object correspondences are decided before the relational mappings are finished. This is largely because in a complex analogy, the number of mappable relations is large compared to the number of object correspondences; indeed the number of mappable relations may have no clear upper bound.

[12] Unless we distinguish the structural rules for generating the candidate set from other conceptual criteria (such as appropriateness, insightfulness, or correctness) that can be applied to the candidate set, we rob analogy of its power to convey new information. Just as we can perform a syntactic analysis of what a sentence conveys, even when the information it conveys is semantically novel or implausible (e.g. "Man bites dog."), so we must be able to derive a structural analysis of an analogy that does not depend on a priori conceptual plausibility. Of course, our ultimate acceptance of the analogy will depend on whether its candidate set of predicates is plausible; but this is a separate matter.

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